Experimental assessment of the quality of ergonomic indicators for collaborative robotics computed using a digital human model

Pauline Maurice, Yvan Measson, Vincent Padois, Philippe Bidaud

Experimental assessment of the quality of ergonomic indicators for collaborative robotics computed using a digital human model

P. MAURICE*†‡, Y. MEASSON†, V. PADOIS‡, and P. BIDAUD‡

† CEA, LIST, Interactive Robotics Laboratory, Gif-sur-Yvette, F-91191, France
‡ Sorbonne Universités, UPMC Univ Paris 06, CNRS, UMR 7222, Institut des Systèmes Intelligents et de Robotique (ISIR), F-75005, Paris, France

Abstract

The growing number of musculoskeletal disorders in industry could be addressed by the use of collaborative robots, which allow the joint manipulation of objects by both a robot and a person. Designing these robots requires to assess the ergonomic benefit they offer. Current methods use *a posteriori* assessment, i.e. observation of the worker, and need a physical mock-up of the robot. Moreover, they exclude dynamic phenomena because their measurements require heavy instrumentation. It has been proposed to use a digital human model, allowing to assess the ergonomic performance of a collaborative robot during the design process. This paper presents preliminary results on three ergonomic indicators formulated to meet the requirements of collaborative robotics. They evaluate respectively the position of the worker, his physical effort and the energy spent during the task. The same manual task is performed by seven human subjects under different time, load and geometric constraints. Each performance is recorded and replayed with a digital manikin in a dynamic simulation framework, in order to calculate the values of the indicators. All three indicators are strongly affected by the geometric parameters in a way that is consistent with ergonomic guidelines. Besides, a linear correlation between the values of the indicators and the penibility perceived by the subjects is observed. Moreover, the results show that the relevance of an indicator is strongly affected by the task features, especially its duration. Future work will be directed towards automatic selection of relevant indicators for a given task.

Keywords: Ergonomics, Digital Human Model, Dynamic Motion Simulation, Collaborative Robotics.

1. Introduction

Though working conditions have improved in developed countries, work-related musculoskeletal disorders (MSD) remain a major health problem. In 2005, MSD represented 59% of the occupational diseases and affected over 35% of workers in Europe (Schneider and Irastorza, 2010). In the US, the total cost of MSD has been estimated around $45 to 54 billion per year (National Research Council and Institute of Medicine, 2001). Hence decreasing MSD is a high-stakes socioeconomic issue.

MSD result from strenuous biomechanical solicitations caused by physical work (Luttmann et al., 2003). Replacing men by robots to accomplish hard tasks might be considered an option. But despite the growing robotization in industry, many tasks cannot be fully automatized because of their unpredictability or their technicality. A solution is to assist the worker with a collaborative robot, rather than replacing him. A collaborative robot enables the joint manipulation of objects with the worker and thereby provides a variety of benefits, such as strength amplification, inertia masking and guidance via virtual surfaces and path (Colgate et al., 2003). To ensure that the use of these devices do decrease the risk of MSD, an ergonomic assessment of the robot-worker system must be performed throughout the design process. Standard ergonomic methods are based on the observation of a worker performing the task (Li and Buckle, 1999), and require a physical mock-up of the robot. Given that this assessment aims at guiding the design, it means a new prototype every time the robot is tuned, which is a significant limitation in terms of cost and time. Besides, these evaluations usually exclude some phenomena that yet affect the risk of MSD, because their measurements require heavy instrumentation of the worker. An alternative is to carry out the assessment within a digital world, where modifications are simpler, and many physical quantities can be accessed at lower cost.

Several tools exist that offer the possibility to perform ergonomic evaluations of a workplace in a virtual environment by simulating the worker with a digital human model (DHM): e.g. Delmia[1], 3DSSPP (Chaffin

[1] www.3ds.com/fr/products/delmia

*Corresponding author. Email: maurice(at)isir.upmc.fr

et al., 2006), Jack, Ramsis, Sammie (Delleman et al., 2004). The manikin is animated through motion capture data, direct or inverse kinematics, or pre-defined postures and behaviors. Various ergonomic assessment methods are included in these software products.The first class of methods estimates the level of risk depending on the exposure to the main MSD factors. The most widely known are RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body Assessment), OWAS (Owako Working Posture Analysis System), the OCRA index (Occupational Repetitive Action), or the OSHA checklist (Li and Buckle, 1999; David, 2005). The second class of methods consists of equations or tables that give physiological limits not to exceed in order to minimize the MSD risk during manual handling operations. The most famous are the NIOSH equation (Waters et al., 1993) and the Snook and Ciriello tables (Snook and Ciriello, 1991), which determine a maximum acceptable load weight depending on the task features.

Though a wide variety of methods are available, they are not suitable for the design of collaborative robots. They must be optimized considering the whole activity and the whole human body. But the tasks which may be addressed by these robots are various and often complex, whereas the existing assessment methods are specific either to a type of activity and/or to a body part. So the evaluation of the entire activity will very likely require the use of several methods, the results of which are mostly not homogeneous and therefore cannot be compared. Moreover, what might be the main drawback of these observational methods is that they are static, meaning that dynamic phenomena are not taken into account. Yet it has been established that fast motions increase the risk of MSD because of the efforts they generate in biological tissues. In collaborative robotics, evaluating the dynamic stages of the activity is even more important because, though designed to be so, the robot is never perfectly backdrivable. Some phenomena can be hard to compensate, even with a dedicated control law. In this case manipulating the robot requires extra efforts from the worker. For instance, collaborative robots providing strength amplification usually are powerful thus heavy: they are highly inertial so leaving dynamic stages out of the assessment can lead to an underestimation of the risk.

Beyond these methods associated with macroscopic human body modelling, some DHM tools provide very accurate biomechanical models including muscles, tendons, and bones, e.g. AnyBody (Damsgaard et al., 2006), OpenSim (Delp et al., 2007). They can calculate quantities such as muscle force or tendon length, which are closely linked to MSD, and sometimes even include dynamic effects. But such models usually require to tune biomechanical parameters, which cannot be properly done without subject specific knowledge of the human body. Besides, these tools provide a measurement for each muscle, tendon, etc... In order to represent the whole body situation these local scores have to be combined in a way that is left to the user to determine. This last criticism also applies to simpler models which provide local measurements such as forces in joints.

The work presented in this paper aims at developing a digital manikin-based ergonomic assessment method fitted for collaborative robots design. This requires the development of both a dedicated ergonomic metric (what to measure) and a measuring tool (how to measure). This paper focuses on the formulation of ergonomic indicators and their use with a dynamic DHM. In section 2 three indicators are defined in order to meet the requirements of collaborative robotics. An experimental validation is conducted to ensure that they are ergonomically consistent: the influence of various work conditions on the indicators values is studied. The protocol is described in section 3. The results are presented in section 4 and discussed in section 5. Section 6 concludes on the relevance of these indicators and the associated DHM and proposes some perspectives about their use within a global assessment method.

2. Definition of indicators

Ergonomic indicators must account for the main MSD risk factors which are strong postural demands, high intensity forces, long exposure duration and highly repetitive exertions. The repetitiveness is omitted in this work because the aim is not the assessment of the real risk for the worker, but the comparison of assistive devices which have no effect on the task frequency.

The postural risk includes two phenomena: the proximity to joint limits and the effort needed to maintain the posture. In reality muscular effort is not due solely to gravity, but also to the dynamic forces associated with the motion, and to the external force caused by the interaction with an object. The former are hardly ever taken into account in existing methods, while the accuracy with which the latter is considered varies much from a method to another. In order to accurately evaluate the effect of an external force on the musculoskeletal system, the repartition of the effort among joints - which depends on the posture - must be computed. In this work a DHM is used to simulate the worker, so unlike with a real human, the driving forces can easily be accessed. A simple rigid-body model with joints actuation is chosen (because as stated previously very detailed models are quite difficult to use), so these forces correspond to joint torques. Since the DHM is animated within a dynamic simulation, the joint torques result from the inverse dynamical model of the manikin. They include all three effects: gravity, dynamics, and external force. Despite their various origins, these three phenomena all have the same consequence on the musculoskeletal system, so they are considered together in the risk assessment. On the contrary, the effect of the proximity to joint limits is of a different kind. Though the combination of several MSD factors increases the risk, the way they interact is not well-established. So it is preferred here to evaluate them separately rather than trying to mix them together.

Since disorders may appear as soon as the solicitations exceed the worker's capacities, a way to estimate the risk is to compare each solicitation with its limit value. For the joints range of motion, the variations from one person to another are small enough to consider mean capacities (Chaffin et al., 2006). However the maximal joint torques vary widely among the population. But assuming that the ratio between torque capacities of different joints is about the same for everybody, the use of mean capacities only scales the indicator value. Since only the variations of the indicator, and no its absolute value, are useful to compare different ways to perform a task, mean capacities are used here to normalize the joint torques (Holzbaur et al., 2005; Chaffin et al., 2006). The influence of joint angles and velocities on maximal joint torques is currently omitted, though models of this phenomenon can be found in the literature (Chaffin et al., 2006). However the influence of force-induced fatigue is included. Instead of being constant throughout the task, the torque capacity is affected by the force exertion according to the following evolution law (Ma et al., 2009):

$$\tau_i^{max}(t) = \tau_i^{max}(0)\, e^{-k \int_0^t \frac{\tau_i(u)}{\tau_i^{max}(0)}\, du} \qquad (1)$$

where k is a fatigue rate assigned to $1\, min^{-1}$, $\tau_i^{max}(0)$ is the nominal torque capacity (before any effort), and $\tau_i^{max}(t)$ and $\tau_i(t)$ are respectively the torque capacity and the torque exerted by the joint at time t.

For both the joint angles and torques, the resulting normalized solicitations on every joint are added to form a score representing the whole body situation. This instantaneous score is time-integrated to provide a score representing the whole activity, taking into account the duration factor. The resulting indicators are I_q for the positions and I_τ for the efforts:

$$I_q = \frac{1}{N} \sum_{i=1}^{N} \int_0^T \left(\frac{q_i(t)}{q_i^{max}} \right)^2 dt \qquad (2)$$

$$I_\tau = \frac{1}{N} \sum_{i=1}^{N} \int_0^T \left(\frac{\tau_i(t)}{\tau_i^{max}(t)} \right)^2 dt \qquad (3)$$

where N is the total number of joints in the body model, T is the duration of the task, $q_i(t)$ and $\tau_i(t)$ are the angle and the torque of joint i at time t, q_i^{max} is the joint angle capacity (joint limit), and $\tau_i^{max}(t)$ is the joint torque capacity at time t defined in equation 1.

These indicators are completed by an energy criterion. In the literature, metabolic energy expenditure is often used to determine the fatigue caused by physical work (Garg et al., 1978). However this physiological measurement cannot easily be computed for a generic task. It requires either a very accurate biomechanical model of the human body to simulate the motion, or the use of tables related to specific activities. Instead the energetic indicator is defined as the total joint energy:

$$I_E = \frac{1}{N} \sum_{i=1}^{N} \int_0^T \mid \dot{q}_i(t)\, \tau_i(t) \mid dt \qquad (4)$$

where $\dot{q}_i(t)$ is the velocity of joint i at time t.

3. Validation of indicators

An experimental validation is carried out to ensure that the above-defined indicators correctly account for the relative exposure level to MSD risks. Human subjects perform a manual task in various conditions while their movements and efforts are recorded. Each case is replayed with a DHM, in order to compute the corresponding indicators values. Their variations are qualitatively investigated to highlight their dependence on the task conditions.

3.1. Experimental protocol

a) Task description: A generic manual task is performed. A seated subject moves a tool along a displayed path while pushing on the work surface with it. The tool is a 200 g and 15 cm long handle held with the whole right hand. The path is a 50 cm square. Two sides are replaced respectively with a sinusoidal line and a sawtooth line, to accentuate the joints dynamics (see Fig. 2). Its size is chosen so that the task demands wide joint clearance yet remains feasible by a seated subject. Performing the task means following the entire path once. The subject is instructed not to use his left arm nor his legs.

b) Parameters: Four parameters vary throughout the experiment: the orientation of the work surface, the position of the seat relative to the work area, the allotted time and the magnitude of the force to be applied.

Table 1: Values of the parameters describing the position of the seat. "H" stands for "Horizontal" and "V" for "Vertical": they refer to the orientation of the work plane.

Height	Distance	Orientation
low: 38 cm	(H) close: 20 cm (V) close: 45 cm	45° right
medium: 52 cm	(H) far: 45 cm (V) far: 75 cm	45° left
high: 66 cm		0° (face on)

The work surface is either horizontal or vertical. The various positions of the worker's seat are described in Fig. 1 and Table 1. The "close" and "medium" values are chosen to match ergonomic guidelines for seated work (Chaffin et al., 2006). All combinations are tested except "horizontal - close - high" because the legs do not fit under or in front of the table, and "45° right" is only done for "close - medium" for reachability reasons.

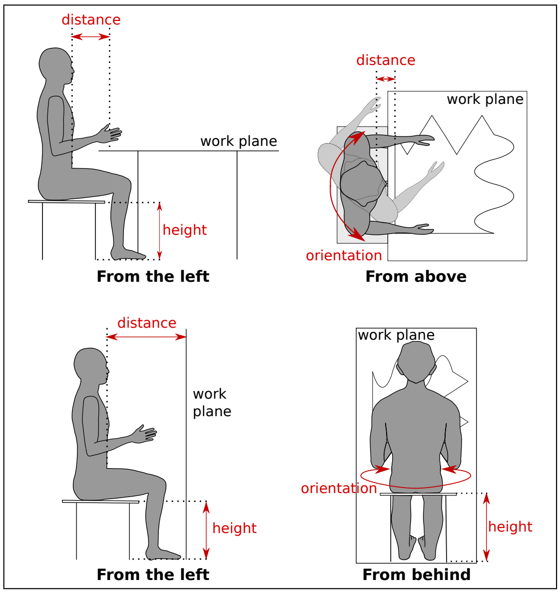

Figure 1: Definition of the parameters describing the position of the worker's seat for the horizontal (top) and vertical (bottom) work planes.

The allotted time and the magnitude of the force define three varieties of the original task, described in Table 2 as "neutral", "force" and "velocity". The force magnitude in the "force" task is slightly lower that the maximal force capacity, calculated for this particular movement according to (AFNOR, 2008). The subject is provided with an audio feedback of the exerted force: low-pitched, high-pitched or no sound when the force is respectively too weak, too strong or within the imposed range. The allotted time is displayed through a progress bar on a screen, and the subjects are instructed to move the tool as regularly as possible along the path.
All three tasks - "neutral", "force" and "velocity" - are performed in random order for both orientations of the work plane and for each seat position. Breaks are regularly allowed to prevent fatigue.

Table 2: Values of the time and force constraints.

Task kind	Allotted time	Mean hand velocity	Force magnitude
neutral	30 s	0,085 $m.s^{-1}$	none
velocity	5 s	0,5 $m.s^{-1}$	none
force	30 s	0,085 $m.s^{-1}$	18 N $\pm$ 1,96 N

c) Subjects: Seven healthy subjects (4 males and 2 females) ranging from 23 to 28 years old perform the experiment for the horizontal work plane, and three of them also for the vertical work plane. Table 3 describes their physical features.
Their movements are recorded with a CodaMotion[2] motion capture device. The subjects are equipped with markers on their torso, right arm and hand, and on the tool. The seat is set on a force platform to measure the contact forces with the ground. The contact forces with the work surface are measured through a force sensor embedded in the tool.
During the experiment, the subjects give each gesture a mark between 0 and 10, depending on how difficult the task is perceived.

Table 3: Physical features of the human subjects: size and body mass index (bmi).

	Size (m)			
	Min	Max	Mean	Std dev
Horizontal plane	1,53	1,83	1,71	0,11
Vertical plane	1,53	1,79	1,63	0,12
	BMI ($kg.m^{-2}$)			
	Min	Max	Mean	Std dev
Horizontal plane	20,9	33,3	24,5	3,9
Vertical plane	21,8	33,3	25,6	5,4

3.2. Indicators calculation

a) Simulation framework: Once recorded and filtered, the data are imported in the XDE simulation framework developed by CEA-LIST [3]. It allows for dynamic simulation and provides a DHM (see Fig. 2) which can be animated through several customizable ways.
The model consists of 20 joints and 45 degrees of freedom. Each DoF is a hinge joint controlled by a sole actuator. The model is automatically scaled according to the size and mass of the subject. Each body segment is further manually modified to match the subject morphology.

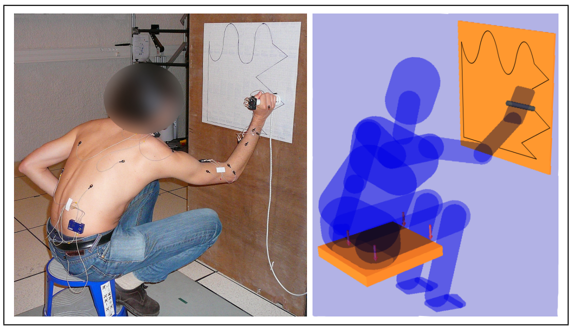

Figure 2: Left: A human subject performs the task while his motion is recorded. Right: The motion is replayed with a virtual manikin within a dynamic simulation framework.

b) Manikin control: The motion is replayed by solving an optimization problem to determine the joint torques which allow to follow the markers trajectories at best, while respecting physical constraints. The LQP controller framework developped by Salini (Salini et al., 2011) is used. Mathematical formulation of the problem is given in equation 5.

[2] www.codamotion.com
[3] www.kalisteo.fr/lsi/en/aucune/a-propos-de-xde

$$
\min_{\tau, w_c} \quad \sum_i \omega_i T_i(\tau, w_c)
$$
$$
w.r.t. \begin{cases} M(q)\ddot{q} + C(q,\dot{q}) + g(q) = S\tau + J_c^T(q) w_c \\ q_{min} \leq q \leq q_{max} \\ \tau_{min} \leq \tau \leq \tau_{max} \\ C_{c_j} w_{c_j} \leq 0 \quad \forall j \\ J_{c_j}\ddot{q} + \dot{J}_{c_j}\dot{q} = 0 \quad \forall j \end{cases} \tag{5}
$$

where τ is the vector of joint torques, w_c the vector of contact forces, q the vector of generalized coordinates of the system, and $\dot{q}$ and $\ddot{q}$ its first and second derivatives. The first constraint is the equation of the dynamical model: M is the inertia matrix of the system, C the vector of centrifugal and Coriolis forces, g the vector of gravity forces, S the selection matrix, and J_c^T the Jacobian of contacts. The second and third constraints are the bounds on joint positions and torques. The last two constraints correspond to the contacts: each contact point c_j must respect the Coulomb friction model, with C_{c_j} the friction cone. The values of the contact forces insuring the balance of the system (here the interaction between the seat and the manikin's thighs) therefore result from the optimization and do not need to be known beforehand. The objective function is a sum of tasks T_i weighted by the coefficients ω_i. It contains four types of tasks:

- Cartesian position tasks $\quad \|J_i\ddot{q} + \dot{J}_i\dot{q} - \ddot{X}^*\|^2$
- Joint position tasks $\quad \|\ddot{q} - \ddot{q}^*\|^2$
- Cartesian force tasks $\quad \|w_{c_i} - w_{c_i}^*\|^2$
- Joint force tasks $\quad \|\tau - \tau^*\|^2$

where the superscript * refers to the desired acceleration/force. The desired force is directly the contact force wanted. The desired acceleration is defined by

$$
\ddot{z}^* = \ddot{z}^{goal} + K_v(\dot{z}^{goal} - \dot{z}) + K_p(z^{goal} - z) \tag{6}
$$

where z is either q or X. K_p and K_v are the proportional and derivative gains. The superscript ^{goal} indicates the position, velocity and acceleration wanted for the body or joint.
In this work, the cartesian position tasks are the markers trajectories. The weights are chosen accordingly to the technique by Demircan (Demircan et al., 2010), though here weighted instead of hierarchical control is used. The markers associated with limbs extremities and the pelvis are given the biggest weight, then the weight decreases when the body is further away from the extremities. Contrarily to inverse dynamics methods, the contact forces with the seat are not imposed here, but result from the optimization problem. So the only cartesian force task is the contact force with the tool. The desired value is given by the force sensor measurement. Low weight joint position tasks are added for the body parts that are not controlled through the markers positions, so that there is no unwanted motion. Finally there is a joint force task which aims at minimizing the joint torques to prevent useless effort. Its weight is very small since it must not hinder the other tasks.

4. Results

The following results depict the variations of the indicators depending on the task features. Values are averaged on all subjects since the indicators are not meant to be subject specific. For the sake of clarity, the values in each figure are normalized by the minimum and maximum values of the addressed case.

4.1. Position Indicator

A linear correlation is observed between the indicator values and the penibility perceived by the subjects when considering tasks of the same duration. The Pearson's correlation coefficients are respectively 0.86, 0.89 and 0.87 for the "neutral", "force" and "velocity" tasks considered separately, and 0.84 for the "neutral" and the "force" tasks considered together. However this coefficient drops to 0.54 when the "velocity" task, which is 6 times shorter than the others, is added. This suggests that the proposed position indicator is only relevant to compare tasks of the same duration.
Comparison within a same task:

- **Seat distance and orientation:** The indicator is higher (t-test, $p = 0.003$) when the subject seats further away from the work area (see Fig. 3), because he has to deviate much from the neutral ergonomic posture (standing upright, arms along the torso, elbows flexed at 80°) to reach the path. What actually matters is the distance from the path to the right hand, which handles the tool. This explains why the "left" orientation seems better than the "face" one (see Fig. 1), and why the "right" orientation, though associated with a "close" position, is roughly equivalent to the "far" cases.

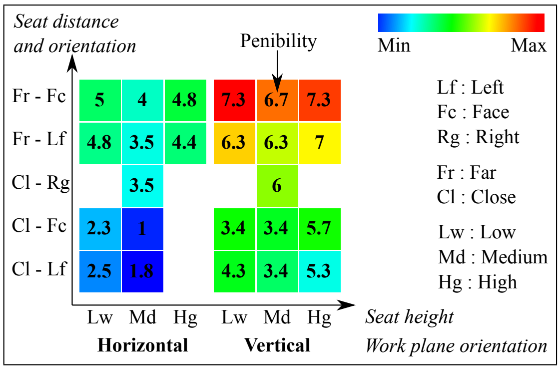

Figure 3: Variations of I_q depending on the position of the subject's seat and the work plane orientation ("neutral" task). The numbers correspond to the penibility perceived (between 0 and 10) by the subjects.

- **Seat height:** In "close" position, the best seat height according to the indicator is the "medium" one when the work plane is horizontal, and the “high” one when it is vertical. These results are ergonomically consistent: in the horizontal case, the “medium” height was chosen in accordance with ergonomic guidelines; in the vertical case, the “high” height requires less work with the arm raised, a position discouraged by ergonomic guidelines.

• **Work plane orientation:** For a same position of the seat, the indicator values are significantly higher (t-test, $p < 0.01$) in the vertical case than in the horizontal one (see Fig. 3). The center of the path is set higher in the vertical case, so it requires the subject to work with the arm raised. Besides the imposed tool orientation (axis normal to the work plane) and whole hand grasp lead to unusual arm angles when the work plane is vertical (elbow upper than shoulder).

Comparison between different tasks: The durations of the tasks are artificially equalled so that the results of the three tasks can be compared. In the “velocity” task, the manikin replays the whole gesture not once but six times in a row. The “velocity” task results in the smallest values of the position indicator (see Fig. 4). The allotted time is so short that the path has to be smoothed, thus requiring less extreme joints angles. On the other hand the difference between the “neutral” and “force” tasks is not statistically significant. Despite the force exertion, the subjects do not modify their posture much, either because it is already strongly constrained by the imposed hand trajectory and seat position, or because the demanded external force is small enough not to require any change in the posture.

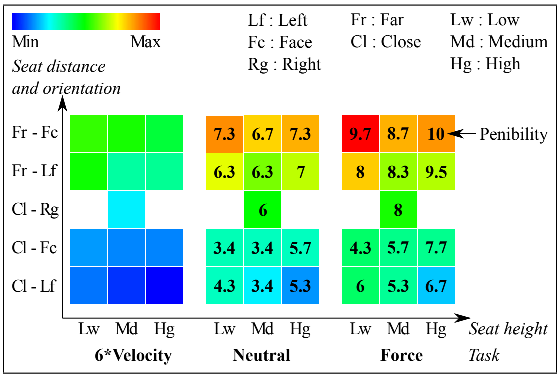

Figure 4: Variations of the I_q depending on the position of the subject's seat and the kind of task (vertical work plane). The numbers correspond to the perceived penibility.

4.2. Effort Indicator

A good correlation between the indicator values and the perceived penibility is observed within a same task (Pearson's coefficient equals respectively 0.81, 0.84 and 0.85 for the “neutral”, “force”, and “velocity” tasks) or when the “neutral” and “force” tasks are considered together (Pearson's coefficient equals 0.81). But the correlation coefficient drops to 0.59 when all three tasks are considered together. As for the position indicator, the proposed effort indicator is not suitable to compare tasks of different durations.

Comparison within a same task: The force indicator is highly affected by the position of the subject relative to the work area, because of the effect of gravity on his body segments (see Fig. 5). The further away the seat is from the work plane, the more the subject must deviate from an upright position, needing higher joint torques to maintain this posture.

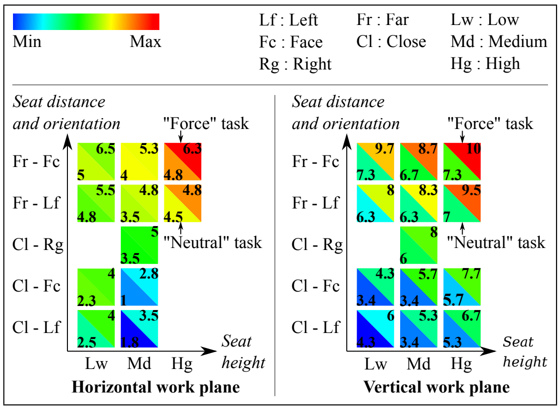

Figure 5: Variations of I_τ depending on the external force and the seat position. Left: horizontal work plane. Right: vertical work plane. The numbers correspond to the perceived penibility.

Comparison between different tasks:

• **External force:** When the work plane is vertical the indicator of the “force” task is significantly higher ($p = 2\,10^{-3}$) than the one of the “neutral” task, whereas they are much more similar ($p = 0.28$) in the horizontal case. Given the direction of the external force, the gravity torques and the external load torques are of opposite signs, so the absolute value of the joint torques does not increase much (and can even decrease) with the force exertion: pushing on the work plane helps balancing. This phenomenon is more noticeable when the work plane is horizontal since the direction of gravity is directly opposed to the one of the external force.

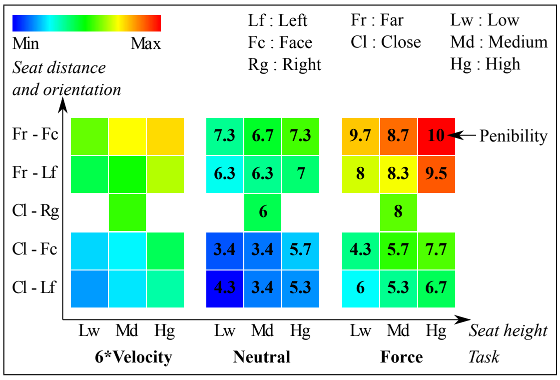

Figure 6: Variations of I_τ depending on the seat position for all three tasks “velocity”, “neutral” and “force” (vertical work plane). The numbers correspond to the perceived penibility.

• **Speed of motion:** As for the position indicator, an artificial “velocity” task is created, which duration equals the one of the other tasks. The indicator of the "velocity" task is significantly higher ($p = 0.019$) than the one of the "neutral" task, because the faster dynamics of the movement induces higher joint torques (see Fig. 6). However, according to the indicator, this increase in the joint torques is not as important as the one due to the external load in the "force" task.

4.3. Energy Indicator

Contrarily to the two previous indicators, the correlation between the energy indicator and the penibility is fairly good when all three tasks are considered together (Pearson's coefficient equals 0.75), and does not improve when each task is considered separately (Pearson's coefficients equal respectively 0.71, 0.86 and 0.70 for the "neutral", "force" and "velocity" tasks). This suggests that the energy indicator is suitable to compare tasks of different duration.

Comparison between different tasks:

- **Speed of motion:** Though the "velocity" task lasts much less than the two others, its indicator is only slightly lower (see Fig. 7, where the real "velocity" task is used). The motion being much faster, the total energy spent is about the same.
- **External force:** Contrarily to the effort indicator (see Fig. 5 left), the energy indicator of the "force" task is often lower than the one of the "neutral" task, especially when the seat is far. This result is quite unexpected because a same allotted time and a very similar posture (see section 4.1.) should lead to same joint velocities for both tasks, and therefore I_τ and I_E should have similar variations. This difference is probably due to the fact that the allotted time is not strictly respected. Because the time constraint is not displayed on the path itself, the subject tends to move slightly slower in the "force" task to better control the force magnitude (especially when his position makes it hard to control).

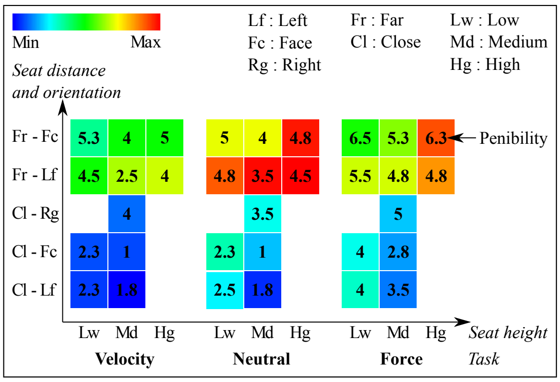

Figure 7: Variations of I_E depending on the seat position for all three tasks "velocity", "neutral" and "force" (horizontal work plane only). The numbers correspond to the perceived penibility.

5. Discussion

According to the previous results, the proposed indicators account quite correctly for the way a task is performed. Their main variations are ergonomically, or at least physically, consistent, and the few unexpected results seem to come from ill-adapted choices in the task definition (external force magnitude and direction, display of the time constraint) rather than from the indicators themselves.

However, all the indicators are not equivalent depending on the task features (i.e. on what is compared). The position and effort indicators are not suitable to compare tasks of different durations, whereas the energy indicator is. On the other hand, when considering tasks of the same duration, the position and the effort indicators account more accurately for the solicitation experienced by the worker than the energy indicator. Their correlation with the penibility perceived is better, except in the "force" task where the energy indicator also shows a good correlation with the penibility. Therefore, previously to carrying out a comparison, it is necessary to select the relevant, i.e. the most discriminating, indicators for the given conditions.

In most cases there may be several relevant indicators. When addressing the position of the seat, the variations of the position and the effort indicators are mainly similar (the closer, the better) and they both show a good correlation with the penibility, so one could be tempted to keep only one of them for their study. However these indicators are not redundant and sometimes bring antagonistic conclusions: for the best seat distance (close - left), the best seat height is the high one according to the position indicator whereas it is the low one according to the effort indicator (see Fig. 3 and 5 right). More generally, the design of a workstation - or a collaborative robot - usually results from trade-offs. So this work does not mix several kinds of solicitations within a sole indicator, because considering antagonistic effects within a same task is easier this way. Several indicators can be used in a multi-criteria optimization in order to design a robot which is as good as possible regarding every MSD risk factors.

Finally, it should be noted that the indicators proposed in this work leave out some important phenomena related to MSD. In particular the co-contraction of antagonistic muscles, which occurs mainly in tasks requiring high precision (Gribble et al., 2003), is not modelled. Consequences of this omission can be observed in the linear relation between the penibility and the effort indicator: the y-intercept is bigger in the "force" task (2.8) than in the "neutral" task (1.8). The increase in the joint torques during the "force" task is underestimated in the simulation because it only takes into account the external load (the manikin is not preoccupied with precision), whereas the human subjects must accurately control the force they apply on the work plane, which requires an additional effort due to co-contraction.

The omission of the co-contraction phenomenon is not due to the indicator formula, but to the representation of the human body, in which each joint is controlled by a unique actuator. However this phenomenon could be modelled without changing the body model, by using a variable impedance in the manikin control (i.e. adapting the gains K_p and K_d in equation 6). A higher stiffness allows a more accurate gesture and corresponds to a higher effort. But this has not been implemented since it requires a control law performing trade-offs between the precision and the exertion, which is out of scope here. Nevertheless, the indicators proposed in this work are not intended for medical purpose (e.g. real exposure level to MSD risk factors) but for guiding the design of assistive devices, so this evaluation, though incomplete, is still a first step in the right direction.

6. Conclusion

Three ergonomic indicators adapted to the needs of collaborative robotics have been proposed. They consider the position and the effort of the worker, and the energy he spends performing a task. An experimental validation has been carried out on seven subjects, in order to study the influence of several task features (geometric, force and time constraints) on the indicators values. The subjects' movements have been recorded with a motion capture system, and replayed with a dynamic DHM to compute the indicators. The indicators show a linear correlation with the penibility perceived by the subjects, and their variations are consistent with ergonomic guidelines and physical considerations.
Those results suggest that the proposed indicators could be used to compare collaborative robots in the design process. However, each indicator provides different information, so their relevance is highly dependant on the task considered. Further work will be directed towards the development of a method for selecting the relevant set of indicators depending on the task features, in order to perform a multi-objective optimization.

References

AFNOR , 2008. NF EN 1005 Safety of machinery - Human physical performance. Association francaise de normalisation.

Chaffin DB, Andersson GBJ, and Martin BJ, 2006. Occupational biomechanics. Wiley, 4th edition.

Colgate JE, Peshkin M, and Klostermeyer SH, 2003. Intelligent assist devices in industrial applications: a review. In: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, 2516-2521.

Damsgaard M, Rasmussen J, Christensen ST, Surma E, and de Zee M, 2006. Analysis of musculoskeletal systems in the AnyBody Modeling System. Simulation Modelling Practice and Theory, 14(8), 1100-1111.

David GC, 2005. Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. Occupational Medicine, 55(3), 190-199.

Delleman NJ, Haslegrave CM, and Chaffin DB, 2004. Digital Human Models for Ergonomic design and Engineering. In: Working postures and movements - Tools for evaluation and engineering. CRC Press.

Delp SL, Anderson FC, Arnold AS, Loan P, Habib A, John CT, Guendelman E, and Thelen DG, 2007. Opensim: open-source software to create and analyze dynamic simulations of movement. IEEE Transactions on Biomedical Engineering, 54(11), 1940-1950.

Demircan E, Besier T, Menon S, and Khatib O, 2010. Human motion reconstruction and synthesis of human skills. In: Advances in Robot Kinematics: Motion in Man and Machine, 283-292. Springer.

Garg A, Chaffin DB, and Herrin GD, 1978. Prediction of metabolic rates for manual materials handling jobs. The American Industrial Hygiene Association Journal, 39(8), 661-674.

Gribble PL, Mullin LI, Cothros N, and Mattar A, 2003. Role of cocontraction in arm movement accuracy. Journal of Neurophysiology, 89(5), 2396-2405.

Holzbaur KRS, Murray WM, and Delp SL, 2005. A model of the upper extremity for simulating musculoskeletal surgery and analyzing neuromuscular control. Annals of biomedical engineering, 33(6), 829-840.

Li G and Buckle P, 1999. Current techniques for assessing physical exposure to work-related musculoskeletal risks, with emphasis on posture-based methods. Ergonomics, 42(5), 674-695.

Luttmann A, Jäger M, Griefahn B, Caffier G, Liebers F, and Steinberg U, 2003. Preventing Musculoskeletal Disorders in the Workplace. World Health Organization. Protecting Workers' Health Series, 5.

Ma L, Zhang W, Chablat D, Bennis F, and Guillaume F, 2009. Multi-objective optimisation method for posture prediction and analysis with consideration of fatigue effect and its application case. Computers & Industrial Engineering, 57(4), 1235-1246.

National Research Council and Institute of Medicine , 2001. Musculoskeletal Disorders and the Workplace: Low Back and Upper Extremities. National Academy Press.

Salini J, Padois V, and Bidaud P, 2011. Synthesis of Complex Humanoid Whole-Body Behavior: a Focus on Sequencing and Tasks Transitions. In: Proceedings of the IEEE International Conference on Robotics and Automation, 1283-1290.

Schneider E and Irastorza X, 2010. OSH in figures: Work-related musculoskeletal disorders in the EU - Facts and figures. European Agency for Safety and Health at Work.

Snook SH and Ciriello VM, 1991. The design of manual handling tasks: revised tables of maximum acceptable weights and forces. Ergonomics, 34(9), 1197-1213.

Waters TR, Putz-Anderson V, Garg A, and Fine LJ, 1993. Revised NIOSH equation for the design and evaluation of manual lifting tasks. Ergonomics, 36(7), 749-776.